DASHBOARD TECHNOLOGY BASED SOLUTION TO DECISION MAKING

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ABSTRACT

The continuing development of DSS applications requires that new technologies be exploited to allow new classes of decision be supported. In most domains, problem-solving and decision-making are overwhelming because of the high volume of complicated data, the multiple complex relationships among data, the negotiability of the constraints, the changing environment, uncertainty and time pressure. Dashboard enables executives to measure, monitor and manage organization performance more effectively this paper proposes a framework for Dashboard DSS that integrates dashboard and Problem solving within enterprise functionality. Finally an DSS system for higher education planning is introduced to illustrate the application of the methodology and evaluate the using of dashboard as a decision making tools.

KEYWORDS: IDSS, Dashboard, MCDM, DASH-DSS

1. INTRODUCTION

Modern decision support systems (DSS) provide their users with a broad range of capabilities. Current DSS facilitate a wide variety of decision tasks including information gathering and analysis, model building, sensitivity analysis, collaboration, alternative evaluation, and decision implementation. Often, DSS are built and used for ad hoc analyses, but increasingly, decision support is integrated into business processes and information systems [2].

Information systems applications that support decision-making processes and problem-solving activities have evolved over the past decades. In the 1970s, these applications were simple and based on spreadsheet technology. During the 1980s, decision-support systems incorporated optimization models, which originated in the operations research and management science.

DSS include many activities in order to create solution's alternatives: e.g. analysis, deduction, projection, comparison, simulation, optimization etc. [1]. In performing these essential activities, DSS utilize many types of the quantitative models. They may be linear programming, integer programming, network models, goal programming, and simulation, statistical models etc, and such models should be implemented in DSS model base subsystems via model management facilities. DSS have recently emerged multiple criteria decision making (MCDM) model embedded DSS and knowledge-based [2].

Many technological and organizational developments have exerted an impact on this evolution. The Web has enabled inter-organizational DSS, and has given rise to numerous new applications of existing technology.

Modern decision support systems (DSS) provide their users with a broad range of capabilities. Current DSS facilitate a wide variety of decision tasks including information gathering and analysis, model building, sensitivity analysis, collaboration, alternative evaluation, and decision implementation.

Often, DSS are built and used for ad hoc analyses, but increasingly, decision support is integrated into business processes and information systems. Most existing computer systems, such as expert systems, decision support systems, and simulation systems, have built-in functionalities and cannot reflect the changing environment and possibilities for negotiation [3]. Problem facing DSS is that the quality of interaction, and the degree of integration possible between human and computer activities, is affected very slowly, if at all, by technological advance.

For problem-solving and decision-making tasks, human beings are the ones who explore the sea of data during problem-solving processes. Thus, dashboard technology faces challenges in dealing with non-geometric data and incorporating human problem-solving processes.

There are many uses for a dashboard to include support of monitoring capabilities, reporting/analysis, and management Dashboards "monitor critical business processes and activities using metrics of business performance that trigger alerts when potential problems arise" The importance of the monitoring purpose is to track performance in various strategic, operational, and financial areas .

This is extremely important for decision-making at executive levels but has a trickle down effect to managers and then accountability in staff [20].

Dashboards allow users to "analyze the root cause of problems by exploring relevant and timely information from multiple perspectives and at various levels of detail". Dashboards can provide management a display of information to improve decisions, efficiency, streamline workflow, and reduce oversight.

A dashboard's strength is also its limitation: it provides only a high-level business overview measured against predefined metrics. This prevents users from asking and answering new questions, and experiencing new relationships between different types of information. Often, users cannot drill down into data to see what is causing the top-line results. Additionally, decisions based on real time dashboard information often exist in a black hole: they are made and executed, but the decision-making process is never passed down through the organization. The result is a need for something beyond the standard dashboard [21].

This research tackles these limitations via trying to model an approach for dashboard shortcoming, and architecting a developmental model Dashboard Decision Support System (DASH-DSS) proposes a variety of visual interfaces to allow access to this data by both experts and non experts. In the decision-making scenario, the quality of decisions made with the assistance of designed dashboard techniques are better than that made without those techniques present, and the differences between the two groups enlarge as the amount of data considered increases. Dashboards provide insight into the planning problem status, potential directions for decision maker to take actions, and evaluations of adjustments. A decision maker using dashboard techniques should perform better during the entire problem-solving process. In fact, this is the ultimate goal of developing dashboard for better decision-making.

This paper seeks to propose an intelligent decision support system framework integrating dashboard frameworks and mathematical models. DASH-DSS framework potentially allows decision makers to move from intuitive decisions to

analysis-based decisions by using a complete hierarchy of objectives, mathematical equations and a simulation of increased capabilities. To illustrate the utility of the proposed framework, this paper aims to apply the framework to a hypothetical decision-making scenario in higher education.

A dashboard system for higher education planning is introduced to illustrate the application of the methodology. The rest of this paper is organized as follows.

Section 2 discusses the state of art for intelligent decision support system and dashboard; in section 3 discusses Analysis of the DSS Survey, Section 4 presents a formulation of our proposed framework called DASH-DSS in Section 4, and formulates implementation of DASH-DSS on higher education. Section 5 concludes the paper and projects a future work.

2. LITERATURE REVIEW AND BACKGROUND

DSS: Architectures and Technologies

Most research efforts reported in the last decade tried to fill the gap of developing IDSS for a variety of domains by using a single intelligent tool and addressed a significant class of decision situations. This section reviews and summarizes the state of DSS architectures and technologies.

A number of articles discuss architectural issues, frameworks, usability, and other technology topics that are generally applicable to DSS.Basically DSS concept has extremely broad definitions, depending on the author's point of view e.g. use, user, and goal; interface characteristics; time horizon and system objective; type of problem structure and system functions; systems components; and development process. For instance see Gorry and Scott-Moton 1971, Little 1970, Alter 1980, Moore and Chang 1980, Bonzek at el 1989, and Keen 1980 respectively [19]. From these definitions, one may define DSS as a computer based information system that can support users during decision life cycle for semi structured problem. Another synonym for DSS is knowledge-based systems, which refers to use knowledge for reasoning. While DSS term stands for Integrated, Interactive and Intelligent; While IDSS term stands for Integrated, Interactive and Intelligent; Due to there are multiple different kinds of IDSS, some assumptions were proposed to replace model base management system with an expert systems (ES)or other alternative intelligent decision making modules, to enhance the model base management system (MBMS), and improved user interfaces (e.g. natural language processing or similar techniques [18, 19]).

IDSS should support wider range of decisions such uncertainty cases make a recommendation. Handle complicated domains, assess of the impact of the proposed solution [4]. Other advantages proposed by Marakas [6] to improve explanations and justifications and formalization of organizational knowledge. Another argues by McGregor [7] who uses an Agent-based DSS attached to the model base instead of to replacing it. An IDSS has been defined as 'a computer-based information system that provides knowledge using analytical decision models, and providing access to data and knowledge bases to support effective decision making in complex problem domains' [8]. The basic concept of an IDSS is the integration of classical decision support including information access and analytical decision models with those of knowledge-based systems including reasoning and inference An IDSS may use models, is built by an interactive process, supports all phases of decision-making, and may include a knowledge component [10]. Knowledge based systems (KBS) embody the knowledge of experts and manipulate this expertise to solve problems at an expert level of performance [9].While Business Intelligence helps in gathering, management, and analysis of large amounts of data [15, 16], knowledge

discovery in Database (KDD) attempts to extract relevant and interesting hidden relationships that exist among variables or between causes and effects [17]. An ideal visualization would provide a set of views [11] using many of knowledge discovery [12] approaches. The search and extraction can be a difficult and exhaustive process [13]. DM remains poorly integrated with the decision support [18] Visual data mining is a step forward [14].

DASHBOARD AND DECISION SUPPORT SYSTEMS

Dashboards conceptually resemble dashboards used in automobiles by simplistically representing the current and past key performance metrics of a company in forms, e.g., gauges, tables and charts.

They are typically showed on one screen, in a web browser, use colors (like traffic light colors) to indicate the progress towards the goal, and use a high data-to-ink ratio (meaning that the pixels which are used for representing relevant information outweigh the pixels used for decorative purposes). They are not a static representation of information, but are updated regularly, for example, hourly, weekly, monthly, quarterly etc., depending on end-user needs and/or capabilities of a system.

They are powerful tools that rely on human cognition principles to improve comprehension with the help of visualization [23], [24], [25]. When referring to the visual features of the dashboards, the main point of reference is Few. Few (2006, p.26)[22] emphasizes the importance of visualization that dashboards provide: "A dashboard is a visual display of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen, so the information can be monitored at a glance." Many guides for dashboard developers recommend to rely on 'gestalt' or i.e. unity principles (such as similarity, proximity, continuality, closure, past experience, a focal point) that leverage human cognition of seeing first the whole and only then the detailed parts. For example, a 'gestalt' principle of proximity refers to a perception of objects that are closer together to be some scholars (e.g., Turban, 2011) [19] refer to Eckerson when providing a definition of what performance dashboards are. Performance dashboard is an umbrella term that holds various types of dashboards like drill-down reports, drillable charts, graphs, and gauge like dashboards. Eckerson (2011, p.11)[20] defines performance dashboard as "a layered information delivery system that parcels out information, insights, and alerts to users on demand so they can measure, monitor, and manage business performance more effectively". This definition recognizes the interactive nature of modern dashboards as the tools powered by business intelligence, their functionality as an information system and the performance management principles they represent. [26]. Figure 1 is an example of some dashboards used in health-care. There is an abundance of vendors that supply businesses with business intelligence based dashboards, to name a few, IBM Cognos, Oracle BI Foundation Suite, SAS Enterprise Intelligence Platform, SAP Business Object BI Platform, MicroStrategy, QlikView and Web Focus [28].

In essence, performance dashboards are information systems for decision support. According to Pauwels et al. (2009)[25], performance dashboards are related to decision support systems (DSS).Yigitbasioglu and Velcu (2011)[23] agree with Pauwels et al. and regard dashboards as data driven decision support systems.

Furthermore, Eckerson (2011) [20] states that on any previously mentioned hierarchical level dashboards can be used for monitoring, analysis, and management. He refers to monitoring as following up the strategy by comparing the desired with the actual performance and sometimes utilizing alert systems for signalling performance deficiencies. Dashboards are then used for analysis to identify what has caused an unacceptable performance. Finally, dashboards are utilized to communicate information across the entire organization for collaboration and decision making.

Literature on performance dashboards mentions monitoring as the most fundamental feature (e.g., Rasmussen et al., 2009; Few, 2006; Yigitbasioglu and Velcu-Laitinen, 2012)[23], [27]. Monitoring means following KPIs and other performance metrics to spot when a corrective action is needed, how good a performance was against a target or/and a benchmark and what can be learnt from this. A consistency in measures is necessary to be able to measure and compare the performance across the organisation and its business units. Planning is setting the goals and strategies for the future. Dashboards can be used for planning, for example, by performing various scenarios, and for sharing the observations, results and strategy with others.

3. ANALYSIS OF THE DSS SURVEY

DSS may employ one or more decision making methods or multiple attribute technique to offer alternatives solution. Some recently developed systems achieved improvement in the implementation of model management, data management, intelligent support, GUI, multiple decision maker, a surveyed various typical DSS tools, prototype and applications to screen what are architecture of DSS, and intelligent techniques are being used; a model base and knowledge base existence, supporting decision group environment attributes, and use of visualized graphical user interface.

According to the surveyed sample in section [2] Although, this reviewed sample may give a good enough focus on DSS, but there many similar studies in the literatures where a diverse of AI methods including artificial neural networks, rule-based expert systems, genetic algorithms and fuzzy inference systems as well as their hybrids is reported. However, this sample is short or may be discussed from different point of views, it presents decision takers' issues for much Intelligence in DSS, Many of intelligent decision support systems rely on different types of information technologies, including model driven DSS, expert systems, multidimensional analysis, query and reporting tools, Group DSS, OLAP (Online Analytical Processing), and Business Intelligence. These techniques more interested in solving problems. The importance of dashboard could be corroborated by the graphical components included in commercial decision support products. While the amount of business information increases at a phenomenal rate; decision makers could easily feel overloaded. Simultaneously, they could also feel the lack of relatedinformation for decisions at hand.

In the next sections we would Identify, address, conceptualize, and develop a work to empower the dashboard components in DSS life cycle, either a decision would be completely taken by a human, or partially by an intelligent agent with a human interfere of who would get a certain level of confidence in the intelligent agent role

4. A PROPOSED DASH-DSS FRAMEWORK

In this section a conceptual model forDashboard Decision Support System (DASH-DSS) is introduced as a Dashboard-based system. Section A presents a block diagram architecture and functionality of the proposed DASH-DSS.

A DASH-DSS Framework

A proposed framework for an DSS dictated to altering the user to decision making opportunity, recognizing problems that need to be solved as a part of decision making, problem solving, and facilitating the user's ability to process knowledge. Moreover, this paper explains a decision-making procedure based on a forecast outcome that predict the effect of actions on future performance, this means predicting both the future environmental state in addition to the change in states caused by different decisions. A proposed DSS architecture composed of three basic components as shown in Figure (1).
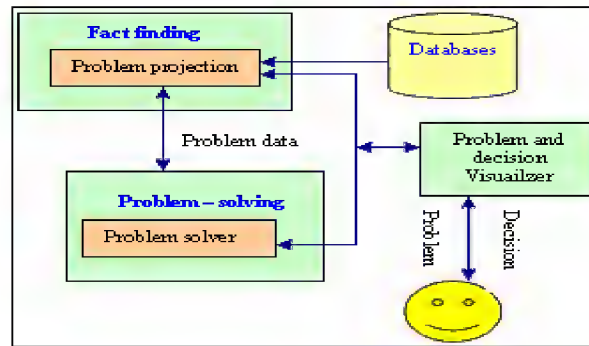
Figure1: A DASH-DSS Framework

Data Management Module

The database management subsystem mainly contains a relational database which is managed by a DBMS, and which provides data retrieval, and updating. A DSS database is a collection of current or historical data from a number of applications or units. The data in a DSS database are usually extracts or copies of operational databases, so using a DSS does not interfere with critical operation systems.

Fact- Finding Module

Fact-finding module using Dashboard (Figure 2) to enables organizations to more effectively. The outer layer of a dashboard is graphical and used as a quick and easy to read monitor of an organization's performance. Next the summary layer helps users to identify the root causes of any problems identified in the outer graphical layer. Finally, the innermost layer is the detailed operational data view which enlightens decision-makers on key actions that may need to be implemented to initiate change, there are many ways that these layers can be depicted to include charts, bar graphs, gauges or even spider diagrams.
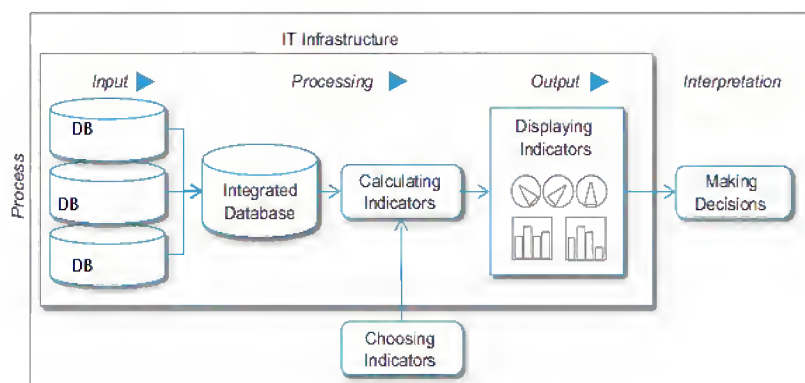

Figure 2: Dashboard Framework

Problem Solving Module

Problem-solving capability is an essential characteristic of an DSS since it is a requirement for supporting decision-making situations. This is beneficially utilized in the proposed DASH-DSS framework.

The problem-solving component figure (3) in the proposed framework receives input from the fact finding component by using color coding techniques and the environment, and includes two sub components: the knowledge base and the problem-solver. The fact finding component provides the knowledge that is incorporated in the knowledge base.

The other input to the problem-solving component comes from the environment in terms of input data essential to solve the decision problem of interest. There are two sets of output from the problem-solving component: solution to the decision-making problem (decision) and information about the problem. The problem solving component uses the knowledge stored in its knowledge base, input from the environment, and necessary problem-solving skills or algorithms it possesses to generate its output.

Problem solving subsystem Includes statistical, management scientific models, or other quantitative models that offers the system's analytical and forecasting capability to predict states. Optimization models, such as linear programming and dynamic programming, may be adopted to determine the optimal resource allocation to maximize or minimize an objective function. Forecasting models can predict future impacts.
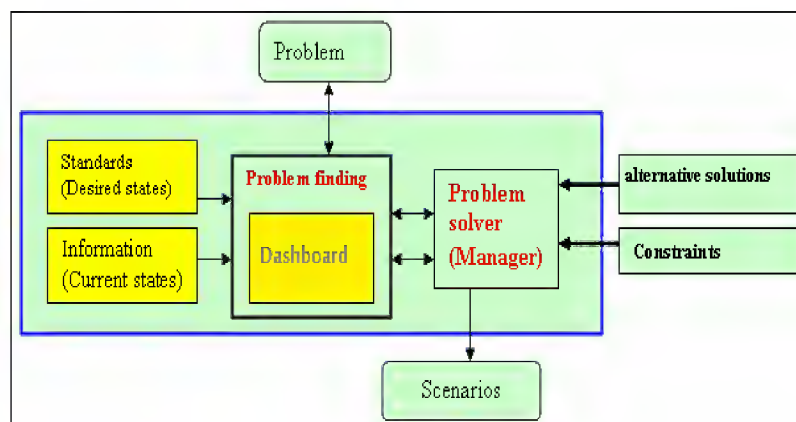

Figure 3: Elements of the Problem Solving Process in Dashboard Contexts

Visual User Interface Module

The graphical user interface was designed with the objective to encourage strictly guided and freewheeling interaction modes. Most decision processes require combination of both approaches. The decision maker would first use analytical tool to explore the facts using color map technique for assuring particular problem areas then apply visualized model for prediction and optimization using knobs, dials, levers and sliders techniques. The inputs of system are filters that recognize sets of relevant features, and every set of such features associates with a set of available actions and outcomes associated with the actions. The set of input features form context and event significance (that something happened and what it means).

Explanatory power of the user interface is assured by providing orientation aids, detailed instructions, graphical support and leading the user through the computation. Visually enhanced presentation of the output facilitates its perception and interpretation. Integration of the data from other sources and accumulation of the data from the past build up a base for refining and extending the analysis.

5. DASH-DSS: HIGHER EDUCATION

We use as a case study the realistic example of the process mointoring and manage the strategic plan decision makers of islamic university (Figure 4).

DASH-DSS is concerned with strategic planning management of university resources and the objectives. Decision-makers are able to evaluate various strategies and generate forecasts by means of simulating with the input data. To keep the model manageable and intuitive and to avoid functional explosion we opted for a single bottle-neck resource of the educational capacity, which is the teaching staff. From experience, staff availability is by far the most crucial resource constraint, expensive and hardly adjustable in the short-term compared to other resources involved, such as facilities, budget, appliances, materials etc.

The following picture are screen shots of prototype for implement a proposed DASH-DSS model in higher education which are used to mointoring the strategic plan.
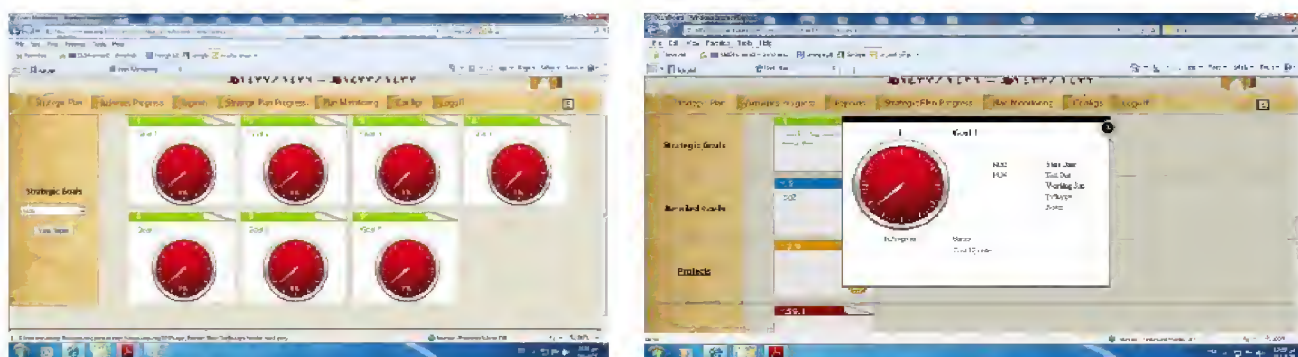

Figure 4: Screen Shot of Prototype for Implement a Proposed DASH-IDSS Model in Higher Education

6. RESULTS OF DASH-DSS FOR DECISION MAKER

This study adopted an experimental method, based on within-subject design approach. dashboard and task complexity are within-subject variables and decision style is between-subject variable. The experiment examined the strengths of dashboard and two types of tasks (fact-finding and problem –solving). In this post experimental questionnaire, each decision maker subject answered their decision styles and assigned extents of

- Strongly Disagree

- Disagree

- Some What Agree

- Agree

- Strongly Agree

To the all questions (factors) of the Evaluation Form the questionnaire data is processed through related descriptive statistics using SPSS. The higher mean (close to 5) indicates that this factor is very satisfactory to users in its functionality. The results are displayed in Table 1. The last column of Table 1, standard deviation, shows that there are lower error estimate and higher reliability in the group of data.

Table 1: Descriptive Statistics

Factors	Sub-Factor	Mean Extent	STDEV
Interactive process	feedback messages valuable	4.52	0.52281
	the solution process is friendly	4.60	0.48989
	easy to interact with the system	4.55	0.58309
	solution process is easy to understand	4.70	0.43588
	make "what-if" analysis	4.82	0.45825
Output format	completeness of output	4.81	0.45825
	output is reliable	4.72	0.54160
	output is relevant	4.68	0.47609
Visualizer guide	necessity of visualizer guide	4.75	0.47609
	usefulness of Visualizer guide	4.78	0.47609
	guide mode suitableness	4.63	0.48989
	easy to use the Visualizer guide	4.82	0.45825
Performance	efficiency of task performance	4.44	0.50990
	enhance the decision making quality	4.47	0.50662
	Flexibility	4.66	0.50662
	GUI	4.64	0.48989
	Effectiveness	4.8	0.5
User attitude	user satisfaction	4.7	0.5
	user confidence	4.79	0.47609

Based on the evaluation results and discussion with the subjects afterwards, this research has summarized the following comments:

- A dashboard is very necessary and helpful to be able to guide decision maker to make a decision; TheDASH-DSS is very flexible. Users can join a decision making process any time, at any location and on any type of computer;

- The DASH-DSS has powerful functionality to match the requirement of decision maker for solving multiple goal decision problems.

CONCLUSIONS AND FUTURE WORK

The study was concerned with the actual extent of introduced the DASH-DSS, a novel interactive multi criteria decision support system that based on Dashboard technology. The DASH-DSS key features are intelligent tools to be used to assist decision-makers answer "what if", questions examine numerous alternatives very quickly and find the value of the inputs to achieve a desired level of output. It would be interesting for future research to investigate about what type of decision purposes dashboards are used for, assess the effects of using dashboard technology on decision making, how dashboards are used in organizations to deal with unstructured information sources. Even though the context of this study is limited to higher education, the results of this study could be generalized to other areas.

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